International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Dealing with Class Imbalance and Multi-Class Classification in Alzheimer's Disease and Dementia: An Innovative Methodology

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Submitted: 16/03/2024 **Revised:** 27/04/2024 **Accepted:** 07/05/2024

Abstract: Alzheimer's Disease (AD) and various forms of Dementia present significant challenges in the field of healthcare, affecting millions of people worldwide. It is crucial to accurately and promptly classify these neurodegenerative disorders to provide effective treatment and care for patients. However, the complex nature of dealing with class imbalances and multi-class classification within the AD and Dementia domain makes it difficult to develop precise diagnostic models. In this paper, we introduce a novel approach BD2EMNET (DEMentia NETwork including Borderline-SMOTE and DenseNet-121 architecture) that simultaneously addresses the issue of class imbalance and handles the intricacies of multi-class classification in the context of AD and Dementia. Through extensive experimentation on diverse datasets, we demonstrated that our approach surpasses the traditional methods. The Traditional methods that are similar to the specified problem were listed in the literature survey and one best experiment among them is first executed and later compared with the proposed approach to indicate the improvement in the performance. Our approach achieves an impressive accuracy of 99.58% for Dementia classification of four class and 99.88% for AD classification of five class. Notably, the approach outperforms existing solutions, particularly in scenarios involving class imbalance and multi-class situation. The implications of the research was profound as it bridges the gap between class imbalance and multi-class complexity, thereby enhancing the accuracy of AD and Dementia classification. This advancement contributes to early detection, personalized medicine, and improved patient outcomes. Furthermore, the adaptability of the approach suggests potential applications in other medical diagnostic contexts facing similar challenges of this. The findings highlight the potential of innovative methodologies to transform disease classification ultimately leading to a more effective healthcare strategies and interventions.

Keywords: *Alzheimer's Disease, Accurate Classification, Class Imbalance, Dementia, Early Detection, Healthcare, Multi-Class Classification, Neurodegenerative Disorders*

1. Introduction

Alzheimer's Disease (AD) stands as the most prevalent form of Dementia. This condition is characterized by a gradual progression, initially manifesting as minor memory impairment and potentially culminating in the inability to engage in meaningful conversations and respond to one's surroundings. AD impacts the regions of the brain responsible for cognition, memory retention, and language proficiency, significantly impairing an individual's capacity to perform their routine daily tasks [1].

Dementia is characterized by a decline in cognitive abilities, including thinking, memory, and reasoning, to a degree that disrupts an individual's daily life and activities. Some individuals with Dementia experience difficulty in managing their emotions, leading to alterations in their personalities. This condition impacts a significant number of people and becomes more prevalent with advancing age (with approximately one-third of individuals aged 85 or older potentially experiencing some form of Dementia). However, it is crucial to note that Dementia is not an inherent aspect of the aging process [2].

Senile, also recognized as Senile Dementia, refers to the decline in mental faculties commonly associated with aging. There are two primary categories of Senile Dementia: one stemming from widespread "atrophy" akin to AD, and the other linked to vascular issues, predominantly strokes. The term Senile Dementia is frequently employed in the context of AD [3].

The intersection of AD and Dementia in the context of medical data highlights a multifaceted problem that necessitates creative solutions. These neurodegenerative conditions, marked by cognitive deterioration, memory impairment, and reduced functionality, present a significant challenge in the worldwide healthcare sector. Ensuring precise AD and Dementia diagnoses is crucial for facilitating timely interventions, enhancing patient care, and advancing our comprehension of disease development [4].

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Table 1. Summary of the papers that worked with the Binary Classification problem.

Authors	*Method*	*Dataset*	*Binary Class*	*Accuracy*
Prajapati *et al.* [5]	DNN	ADNI	AD/CN MCI/CN AD/MCI	85.19% 76.93% 72.73%
Basaia *et al.* [6]	Modified CNN	ADNI	AD/HC	99%
Wang *et al.* [7]	Ensemble Method	ADNI	MCI/AD MCI/Normal AD/Normal	93.61% 98.42% 98.83%
Basheera *et al.* [8]	CNN	ADNI	AD/CN	100%
Richhariya *et al.* [9]	Universum Support Vector Machine based Recursive Feature Elimination (USVM-RFE)	ADNI	CN/AD	100%
Alinsaif *et al.* [10]	Shearlet-based descriptors and deep features	OASIS	CN/AD	80%

However, successfully navigating the complexities of categorizing AD and Dementia at various stages presents a significant challenge. The datasets used to build diagnostic models often grapple with a common issue known as Class Imbalance. This problem arises when the distribution of data samples among different classes is uneven, leading to a shortage of data for crucial categories. In the context of classifying AD and Dementia, this imbalance creates a central obstacle. Since the majority of samples come from individuals without these conditions, the minority are those affected by them. This imbalance adversely affects the learning capabilities of Machine Learning and Deep Learning (DL) models, resulting in biased and less than optimal results.

Addressing the imbalance in medical datasets is crucial for ensuring the accuracy and dependability of diagnostic models. In the context of classifying AD and Dementia, this means having the capacity to recognize subtle differences that set apart different stages of these diseases. This increased precision not just improve predictions but also has the potential to enhance patient prognoses. However, the importance of tackling class imbalance goes beyond just improving diagnostic effectiveness. It also has ethical implications, as biased models could unintentionally contribute to unequal access to healthcare and interventions.

This study conducts a thorough examination of the intricate relationship between AD, Dementia, and the issue of class imbalance in medical datasets. Additionally, we broaden our inquiry to encompass the complexities of Multi-Class classification. This task involves not only distinguishing between individuals with and without the diseases but also discerning between various disease stages and subtypes. Through a detailed analysis, we emphasize how these multifaceted challenges can impact the accuracy of diagnosis and patient care. Moreover, we review existing methods aimed at addressing class imbalance and emphasize the need for innovative approaches capable of effectively addressing the intricacies of multi-class classification in the context of these medical conditions.

By exploring the intricate relationships between AD, Dementia, issues related to class distribution, and multi-class classification, our aim is to make a valuable contribution to the growing field of research that harnesses the capabilities of ML and DL. Our ultimate goal is to improve the accuracy and effectiveness of AD and Dementia classification, thus furthering our ability to effectively address these debilitating conditions.

1.1. Motivations

Our research is driven by the pressing necessity to tackle the complex issues presented by AD and different types of Dementia in the realm of medical data. The sense of urgency arises from the extensive repercussions of these neurodegenerative conditions on both individuals and their families. With the rising prevalence of cognitive decline and reduced functionality, there is a crucial demand for precise and prompt diagnostic approaches to enable effective interventions and enhance patient care.

Nonetheless, the existence of an imbalanced distribution of classes within medical datasets, notably the insufficient representation of minority classes linked to distinct stages of AD and Dementia, poses a challenge for creating accurate diagnostic models. Additionally, the intricacy of performing multi-class classification, which demands precise discrimination among different subtypes of diseases, further compounds this challenge.

We are driven by the desire to close these disparities by introducing a novel method that tackles both the issues of class imbalance and multi-class classification concurrently. Our goal is to elevate the precision of AD and Dementia diagnoses, which could potentially lead to a transformative shift in disease categorization and ultimately result in better patient results.

1.2. Contributions

We present an innovative method designed to tackle the complexities associated with AD, different types of Dementia, imbalanced distribution of classes within medical datasets, and the intricacies of multi-class classification, all at once. Our research integrates these aspects into a unified framework, providing a holistic solution that caters to the unique challenges of disease categorization.

- Our research makes a significant contribution to the advancement of disease classification methodologies in diverse medical scenarios by creating a comprehensive solution to address both class imbalance and multi-class challenges.
- We utilize cutting-edge methodologies from the realms of ML and medical research to offer valuable insights, contributing to the advancement of knowledge and the improved management of intricate neurodegenerative conditions.

- Our approach produces synthetic samples in close proximity to class boundaries, resulting in well-balanced datasets that faithfully capture a wide range of disease stages and subtypes.
- Our study reveals significant enhancements in accuracy when classifying AD and Dementia.

1.3. Organization Of Paper

The document is organized into several sections. In Section 2, an extensive examination of prior research is presented, serving as a basis for the current study. Section 3 provides a detailed discussion of the proposed model, including details about the dataset used and the problem statement. Section 4 delves into an evaluation of the model's performance, drawing comparisons with the baseline model. Ultimately, Section 5 offers a concise summary of the accomplishments of the model.

2. Related work

This portion of our paper acts as a link connecting our research to the wider academic conversation. It serves as a navigational tool, leading readers through the established scholarly terrain, emphasizing the distinctive elements of our study, and aiding in situating our work within the broader research community.

In recent years, a variety of ML and DL techniques have surfaced as valuable tools in aiding the diagnosis of AD. These technologies offer support to healthcare professionals by providing them with essential information to make well-informed choices regarding treatment [11]. In this segment, we have pinpointed and underscored the relevant articles related to the topic, highlighting their drawbacks.

We have categorized the pertinent literature into two distinct groups: one focusing on Binary Classification, and the other on Multi-class problems. While Binary Classification boasts a substantial body of research and findings, Multi-class problems, which entail the consideration of three or more classes within the context of a particular disease, have received comparatively limited attention in the literature.

2.1. Binary Classification

The performance attained in Binary Classification tasks up to this point has exhibited encouraging outcomes. Substantial research has indicated that modern ML and DL models possess the ability to attain remarkable levels of accuracy when distinguishing between two separate categories. These accomplishments emphasize the efficiency of sophisticated methodologies, resilient feature development, and careful model optimization. Numerous investigations have documented accuracies significantly surpassing the initial benchmarks, affirming the capacity of these models to reliably categorize binary results. Table 1 gives the summary of the review related to Binary Classification.

2.2. Multi-Class Classification

Nevertheless, when we shift towards more intricate Multi-Class classification situations, like those encountered in AD and Dementia studies, the terrain becomes inherently convoluted. The subtleties introduced by various disease stages and subtypes pose a significant challenge to the models' capacity to sustain their prior accuracy levels. Moving from Binary to Multi-Class classification demands a fresh outlook, requiring customized methodologies capable of effectively handling the complexities inherent in the problem. Table 2 gives the summary of the review related to Multi-Class Classification.

While achieving significant results in Binary Class classification is certainly commendable, it is imperative to acknowledge the necessity for fresh strategies tailored to address the intricacies associated with Multi-Class scenarios. Our research endeavors to fill this void by introducing a novel approach that not only upholds remarkable accuracy but also broadens its utility to encompass Multi-Class classification, especially within the realm of AD and Dementia. Drawing upon the accomplishments of binary classification and customizing them to suit the Multi-Class domain, our aim is to make a meaningful contribution to the enhanced comprehension of these intricate diseases and their various stages.

Table 2: Summary of the papers that worked with the Multi-Class Classification problem.

Authors	***Method***	***Dataset***	***Multi-Class***	***Accuracy***	***Drawbacks***
Murugan *et al.* [11]	DEMNET	Kaggle	MID/MOD/ND/VMD	95.23%	Accuracy is yet to increase.
Basheera *et al.* [8]	CNN	ADNI	AD/CN/MCI	86.7%	Accuracy is yet to increase.
Neetha *et al.* [12]	D-DEMNET	ADNI	AD/lMCI/MCI/eMCI/NC	95.16%	Comparatively, it is less effective in five class classification.
Raju *et al.* [13]	Transfer Learning with VGG16 using Fastai	Kaggle	MID/MOD/ND/VMD	99%	Yet to try on higher class.
Wang *et al.* [7]	Ensemble Method	ADNI	AD/Normal/MCI	97.52%	For three-Class.
Suganthe *et al.* [14]	Combination of Inception and ResNet V2	Kaggle	MID/MOD/ND/VMD	79.12%	Accuracy is yet to increase.

3. Proposed Work

3.1. Problem Statement

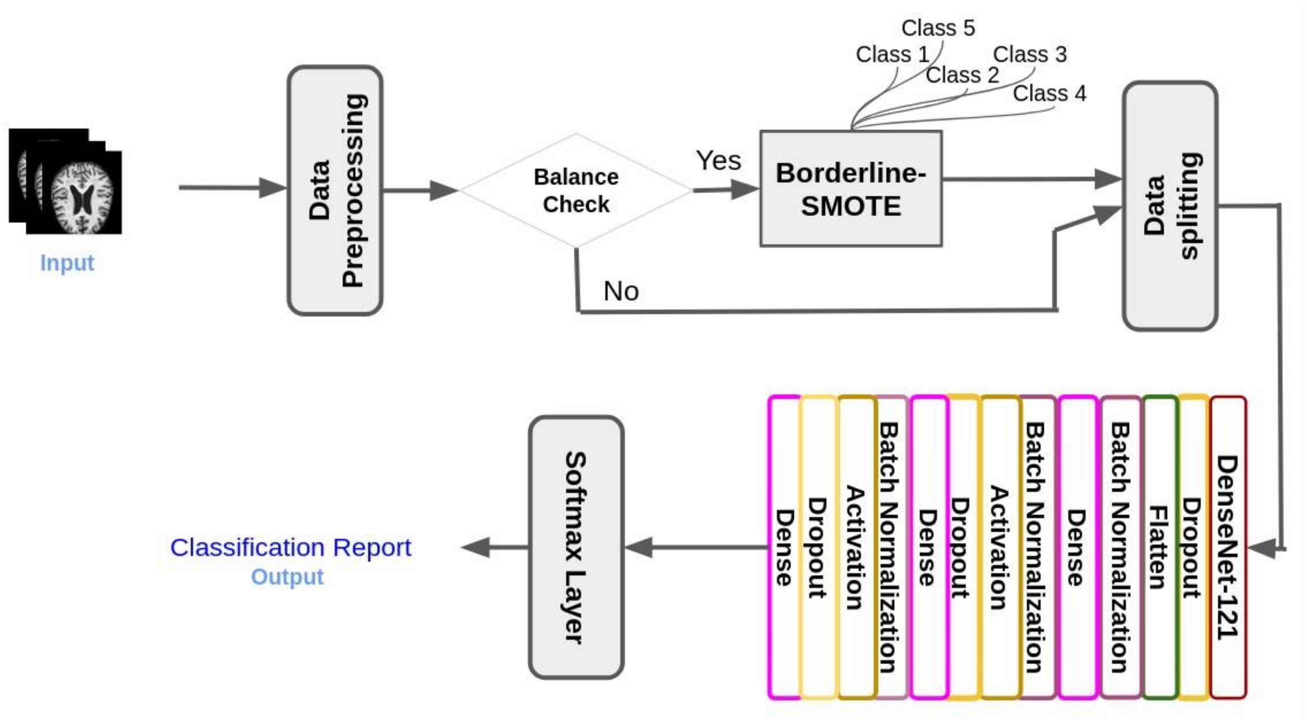


Fig. 1. BD2EMNET Architecture

The early identification of AD and Dementia presents an opportunity for timely intervention, support, and planning. However, this endeavor is not without its challenges, necessitating comprehensive approaches to deliver holistic care and enhance the overall well-being of those impacted by these conditions. To improve the detection of AD and Dementia through DL techniques, it is crucial to address the issue of class imbalance within the dataset. Class imbalance occurs when one category, such as healthy individuals, significantly outweighs another category, like individuals with AD, in terms of data samples. In the context of AD classification, this problem arises due to the scarcity of positive cases (individuals with Alzheimer's) compared to negative cases (healthy individuals) in real-world datasets.

Our objective was to improve the classification performance of our predictive model by ensuring a balanced representation of all classes in the dataset focussing on Multi-Class classification.

3.2. Dataset Description

In our research, we initiated our investigation by obtaining established datasets, which encompassed the four-class Dementia dataset from Kaggle and the five-class AD dataset sourced from ADNI. To ensure the datasets were suitably prepared for analysis, we carried out essential preprocessing procedures. Following that, we tackled the issue of class imbalance that was evident within these datasets.

In order to address the issue of class imbalance, we utilized the Borderline-SMOTE (Borderline-Synthetic Minority Over-sampling Technique) method. This strategy enabled us to create extra MRI images tailored to the underrepresented groups in each dataset. Through the oversampling of these minority categories, our objective was to equalize the distribution of classes and alleviate the adverse effects of class imbalance on the performance of our model.

After conducting the oversampling procedure, our next step involved splitting each dataset into three separate categories: training, testing, and validation sets. This partitioning strategy was crucial to guarantee that our model received ample training data, was evaluated on unseen data, and was validated on a distinct subset.

3.2.1. KAGGLE

Dementia is a degenerative ailment, and its presentation can vary significantly among individuals. Although the rate of progression may vary, most people typically undergo stages of Dementia characterized by specific symptoms. The data related to Dementia was collected through the use of Kaggle [15], a freely accessible open-source platform. In total, the dataset comprises 6,400 MRI images, with each image classified into one of four categories: Mild Dementia (MID), Non-Dementia (ND), Moderate Dementia (MOD), and Very Mild Dementia (VMD). These images were resized to dimensions of 64 x 64 pixels.

Understanding the distinct phases of Dementia is essential for offering suitable care and assistance to individuals impacted by the condition. Detecting and intervening early can enhance the well-being of both Dementia sufferers and their caregivers. Our goal is to utilize the provided datasets, conduct research, and analyze data to acquire valuable insights into Dementia's advancement, with the intention of creating efficient approaches for early identification and therapeutic interventions.

3.2.2. ADNI

The Alzheimer's Disease Neuroimaging Initiative (ADNI) represents a lengthy and collaborative research endeavor conducted across multiple centers [16]. The primary objective is to advance the identification of biomarkers for the early identification and monitoring of AD, encompassing clinical, imaging, genetic, and metabolic aspects. This pioneering partnership between public and private sectors has continued for more than a decade, making substantial and noteworthy contributions to the field of Alzheimer's research through its global facilitation of data sharing among scientists. The ADNI dataset divides AD into five distinct categories, namely eMCI, MCI, lMCI, AD, and NC. This dataset comprises a total of 1296 images, which have been resized to dimensions of 64 x 64 to fit the model's requirements [17].

3.3. Data Balancing using Borderline-SMOTE

Imbalanced classification involves creating predictive models for datasets where one class significantly outnumbers the other. Dealing with imbalanced datasets presents challenges because many ML methods tend to neglect the minority class, resulting in suboptimal performance, even though it is often the most critical class. One approach to address this issue is oversampling the minority class. A straightforward technique involves duplicating instances of the minority class, but these methods do not offer novel insights. Alternatively, it is possible to generate new instances by synthesizing existing ones.

An often employed improvement to the SMOTE technique (Synthetic Minority Over-sampling Technique) involves the identification of misclassified instances within the minority class. This can be achieved through the utilization of a k-nearest neighbor classification model. By directing our attention towards these challenging instances, we can strategically perform oversampling, thereby enhancing precision where it is most required. The initial step of this algorithm involves the classification of observations within the minority class. If all the neighbors of a minority observation belong to the majority class, it is designated as a noise point and is subsequently excluded during the synthetic data generation process, akin to how DBSCAN operates. Furthermore, certain points are categorized as border points if they have both majority and minority class neighbors, and these points are resampled in their entirety.

To address the issue of imbalanced classes, the Borderline-SMOTE technique [18] employs a strategy of duplicating minority class instances at random. This effectively mitigates the class imbalance problem within the dataset. The oversampling of the minority class was carried out using a seed size of 42. Leveraging this approach offers several benefits, including the prevention of overfitting and reduction in information loss.

3.4. BD2EMNET Architecture

In this study, we investigate the fundamental model discussed in prior research and strive to enhance it. Our initial step involves reproducing the original DEMNET model detailed in reference [11], followed by the introduction of our improved architectural modifications. Graphs were generated for each variation, enabling a comparative assessment that highlights the effectiveness of our newly proposed design. The workflow of our suggested BD2EMNET architecture, comprising four main phases, is depicted in Fig. 1.

- Data Pre-processing: During this stage, we carry out essential data preparation procedures, such as data cleansing, standardization, and extracting relevant features. This guarantees that the input data is appropriately structured for subsequent processing.

- Borderline-SMOTE for Dataset Balancing: It is essential to tackle the issue of class imbalance in the classification of AD/Dementia. To create a more balanced dataset, we employ the Borderline-SMOTE method, which generates synthetic instances for the underrepresented classes while maintaining the class boundaries intact.

- D-DEMNET Block: At the core of our proposed approach, we utilize the D-DEMNET block, leveraging the capabilities of the Densenet121 architecture to extract meaningful and distinctive features from the pre-processed and augmented data. This element plays a vital role in enhancing the model's ability to distinguish between different categories. Following the dataset partitioning, our proposed architecture includes a single Densenet121[19] module, three Dropout layers, a Flatten layer, three Batch Normalization layers, three Dense layers, and two Activation layers. The softmax layer is utilized as the classification layer. ReLU is selected as the Activation Function for the hidden layers, which is a commonly employed choice [20]. The optimization process is carried out using the Adam optimizer.

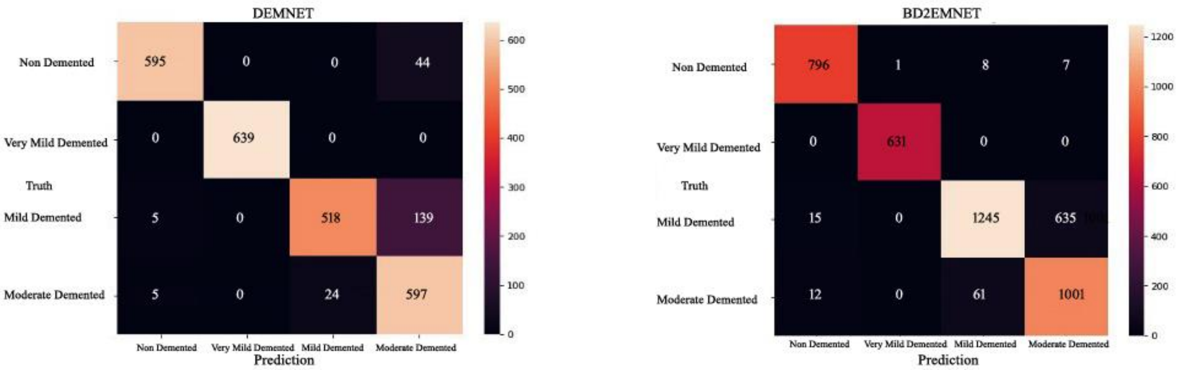
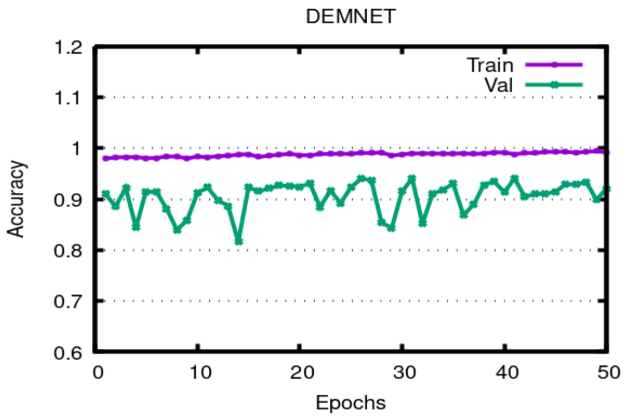
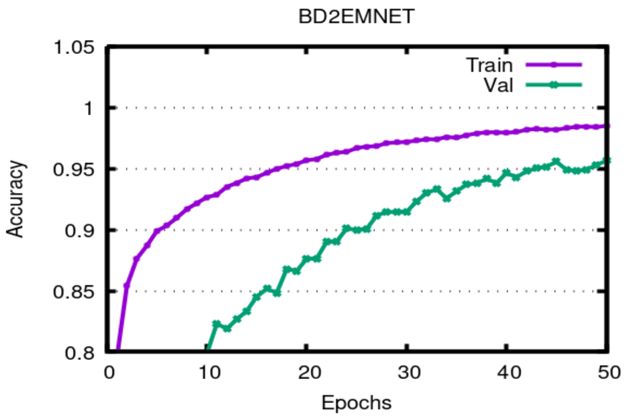


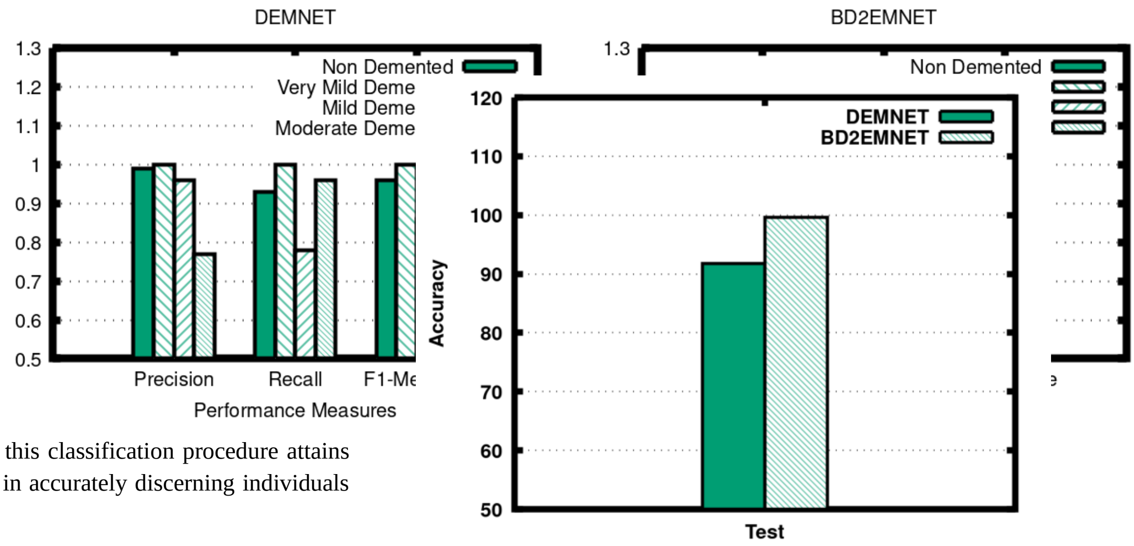
Fig. 3. Comparison of Confusion Matrices for Two Distinct Architectures

International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Classification: In the last stage, the extracted characteristics are inputted into a classification algorithm to forecast AD/Dementia categories. Utilizing the distinctive features acquired from the D-







DEMNET module, this classification procedure attains improved accuracy in accurately discerning individuals with AD/Dementia.

Through the integration of these stages, our BD2EMNET design exhibits a significant enhancement in the accuracy of classifying AD/Dementia. This holistic methodology, which includes data balancing, in-depth feature extraction, and proficient classification, plays a pivotal role in enhancing the dependability and precision of predictions, ultimately assisting in the timely identification and treatment of AD. The model showcases a thorough and systematically organized strategy for tackling the

complexities associated with Dementia classification using MR images. Let's recapitulate the primary phases and constituents of our proposed system:

- Data Collection and Preparation: The AD dataset comprising five classes was sourced from the ADNI database where the four class dataset were obtained from Kaggle. Subsequently, the acquired datasets underwent a series of preprocessing procedures aimed at priming the data for the training phase.
- Dataset Oversampling: To address the challenge of class imbalance, we adopted the Borderline-SMOTE method to conduct oversampling for the underrepresented minority groups in each dataset. This approach aimed to attain a fairer distribution of class frequencies throughout the datasets.
- Data Splitting: The datasets were divided into separate training, testing, and validation sets. This division allowed for a precise evaluation of the model's performance on data it had not encountered before.

Fig. 4. Examining Average Precision, Recall, and F1-score in Comparison of Individual Classes in both Architectures.

- Model Training Process: We employed a DenseNet-121 architecture, which we customized by adding extra layers such as Dropout, Flatten, and various others as depicted in Fig. 1. We selected this configuration to enhance the efficiency of the model's training process. This strategy enabled the model to autonomously differentiate between various categories of MR images by leveraging the unique features present in the dataset.
- Epoch-Based Training: The model underwent 50 epochs during the training process, which allowed it to improve its understanding of the unique features present in the MR images and how they relate to the specific datasets.
- Evaluation and Validation: The evaluation of the model's effectiveness was conducted using the test dataset, utilizing various metrics such as classification accuracy, precision, recall, F1-measure, and confusion matrix [21]. Additionally, validation processes were employed using samples from the training dataset to gauge the model's capacity for effective generalization.

In general, the project showcases a resilient and automated method for categorizing MR images related to Dementia and AD. It harnesses the capabilities of DL to effectively manage intricate data, resulting in a remarkable level of accuracy when distinguishing various Dementia and AD categories [22].

4. Performance Analysis

4.1. Experimental Setup

The proposed model underwent testing on a Windows 10 platform, employing a device equipped with an Intel(R) Xeon(R) CPU running at 2.30GHz and utilizing the Colab Pro service featuring a Tesla P100-PCIE-16GB GPU. Training for the model encompassed 50 iterations, commencing with an initial learning rate of 0.001. TensorFlow version 2.7 served as the primary framework, accompanied by the Python language and several essential libraries including keras, pandas, numpy, and matplotlib. The algorithm's training process was facilitated through the application of the Adam optimizer.

The results were derived by combining information from two separate datasets. To enhance the clarity of our presentation, we structured this section into three distinct subsections aligning with our understanding of the system. To conduct experiment, we made use of essential Python libraries like pandas, NumPy, and matplotlib. The Kaggle dataset encompasses four image classes derived from data abstractions, whereas the ADNI dataset comprises five such classes. Concerning the training data, the Kaggle dataset boasts 6400 MRI images, while the ADNI dataset contains 1296. We will elucidate our approach to preparing these datasets in three sequential stages as follows:

- Training dataset: The training data is employed to construct the model, compute loss values, and fine-tune the weight parameters.
- Validation dataset: The validation set plays a crucial role in the process of choosing the optimal training model. It does so by evaluating the model's performance while adjusting hyperparameters, and it sets aside 10% of the training data exclusively for this validation task.
- Testing dataset: The testing dataset is employed to assess various classifiers and establish the overall accuracy.

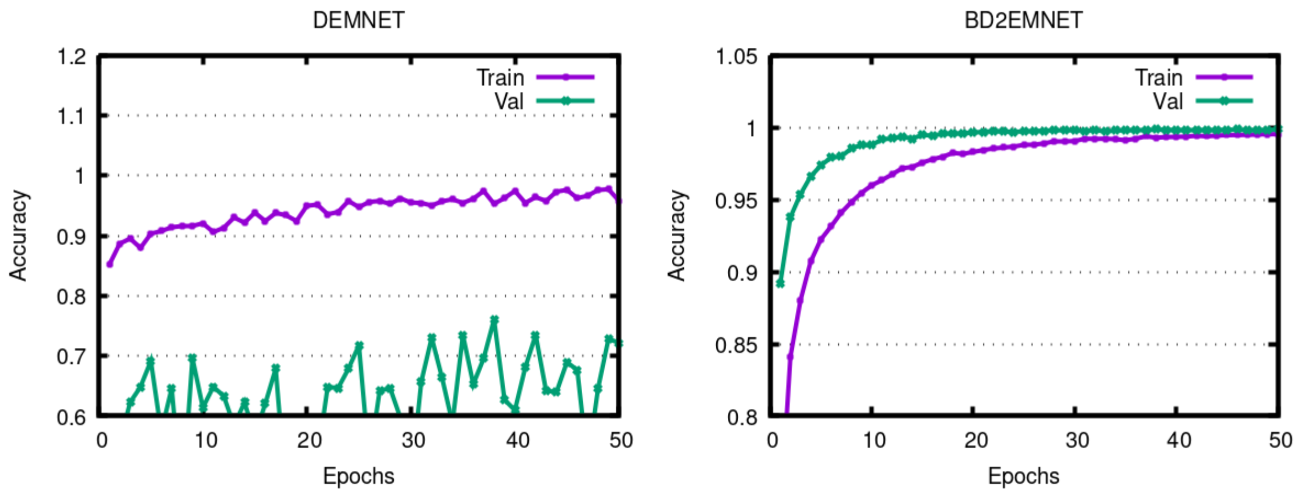


Fig. 7. Comparative Confusion Matrices for Two Distinct Architectures in Five Class

4.2. DEMNET and BD2EMNET for Four Class Dataset

The methodology employed in this study utilizes a four-class dataset, adhering to the dataset's recommended procedures for performance evaluation. To conduct a comparative analysis, we incorporated the SMOTE technique into two architectures: the DEMNET architecture[11], and the novel BD2EMNET architecture. Both architectures were applied to the same four-class dataset. Initially, we established a baseline model with a slight modification involving an image size of 64 * 64 pixels.

Subsequently, we compared the performance of this baseline model with the results achieved by employing our proposed architecture while maintaining the same image dimensions of 64 * 64 pixels.

The Borderline-SMOTE technique, when employed in the proposed architecture, achieves a validation accuracy of 99.58%, with an overall training accuracy of approximately 98.51%. Notably, the testing set used for model validation contains previously unseen images, ensuring a robust evaluation of the trained models. Fig. 2 provides a visual representation of the training and validation curves for both architectural variants. It is worth highlighting that our model exhibited a significantly higher learning rate compared to the base model.

Fig. 3 illustrates the utilization of DEMNET and BD2EMNET architectures in constructing a confusion matrix for the purpose of classifying Dementia stages and predicting AD outcomes. The confusion matrix displays the expected class labels alongside the assigned labels for the four distinct Dementia types. This analysis encompasses a total of (i) 812 images from the ND category, (ii) 631 images from VMD, (iii) 1323 images from MD, and (iv) 1074 images from MOD.

The overall performance metrics, including recall, precision, and F1-score, were computed for MOD, MD, ND, and VMD using the test dataset, revealing encouraging outcomes from this assessment. Fig. 4 provides a visual comparison of precision, recall, and F1-measure for each individual class in both architectures, demonstrating significant improvements achieved by our approach. The BD2EMNET architecture achieves an impressive testing accuracy of 99.58% on the evaluation dataset. Fig. 5 illustrates a comparative analysis of the outcomes. Moreover, it has been observed that in the domain of image processing, Borderline-SMOTE surpasses the effectiveness of the conventional SMOTE technique. These findings highlight that our architecture not only enhances learning but also effectively mitigates class imbalance issues by reducing overfitting, improving feature differentiation, and demonstrating robustness to noise.

4.3. Comparison of DEMNET and BD2EMNET for Five Class Dataset

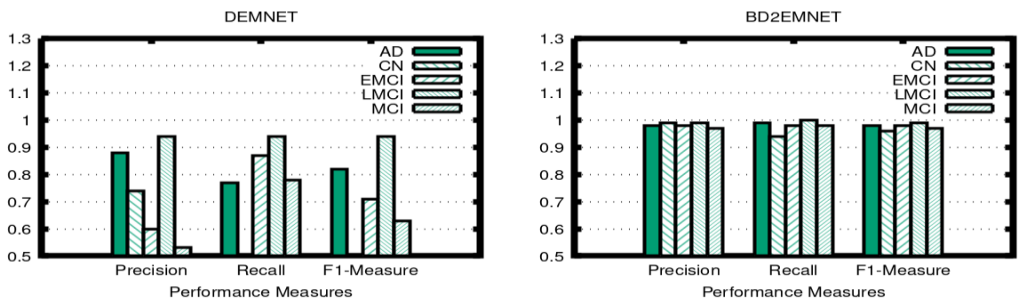
To evaluate the performance of the BD2EMNET architecture on different MRI datasets associated with AD, following its successful performance on the Kaggle dataset, an experiment was carried out. This experiment entailed classifying AD into five distinct categories using data sourced from the ADNI database [12]. The analysis encompassed five distinct AD categories: NC, eMCI, MCI, lMCI, and AD.

Fig. 8. Assessment of Average Precision, Recall, and F1-score in Five Class Dataset.

The proposed approach involved incorporating the Borderline-SMOTE technique into the framework, which yielded a validation accuracy of 99.88% and an overall training accuracy of approximately 99.54%. To evaluate the models after training, a separate test dataset, comprising previously unseen images, was utilized. The training and validation curves for this dataset can be observed in Fig. 6. Furthermore, Fig. 7 provides a visual representation of the confusion matrix generated through the utilization of the BD2EMNET architecture in comparison to the base model. This matrix effectively demonstrates the combined application of the Borderline technique and classification methods for the categorization of various stages of AD, as well as for making predictions about AD. It offers insights into the expected and labeled categories for the five distinct AD types. The evaluation metrics, such as recall, precision, and F1-score, demonstrate promising results for specific categories, as shown in Fig. 8. Notably, the BD2EMNET architecture achieves an impressive testing accuracy of 99.88%, as depicted in Fig. 9. The observation from the base model can be done that the accuracy decreases while the number of classes increases.

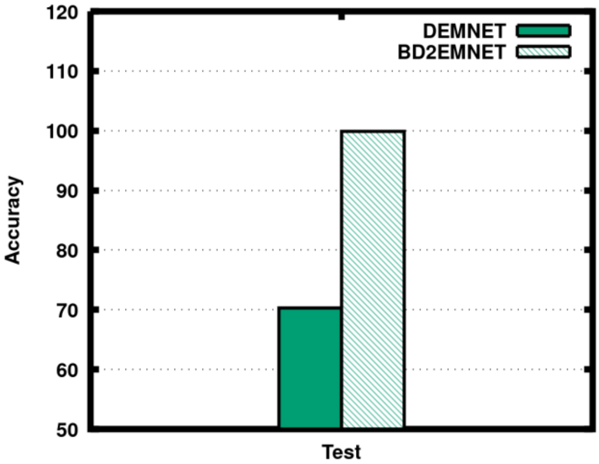
It is observed that the base model achieves utmost 93% in four classes and utmost 71% in five class situations. This notifies that the model performance decreases as the number of classes increases. In contrast, the enhanced architecture remains utmost an equal in performance which is 99% in both four and five class problems. By this observation, we can expect that the architecture has efficient learning abilities even in higher classes.

The results obtained from the classification of five distinct categories indicate that the BD2EMNET model surpasses the DEMNET model in terms of accuracy, precision, recall, and F1-measure. Additionally, it is worth noting that Borderline-SMOTE proves to be more effective in image processing compared to the SMOTE technique. These observations suggest that our architecture enhances learning, addresses class imbalance issues



by mitigating overfitting, improves feature discrimination, and exhibits resilience to noise.

5. Conclusions and Discussions



In summary, our study presents an innovative framework that has shown impressive efficacy in tackling issues associated with class imbalance, enabling precise classification of AD and Dementia datasets encompassing both five-class and four-class scenarios. The importance of early and accurate AD detection cannot be emphasized enough, as it paves the way for timely interventions, efficient management, and enhanced patient care.

Our architectural design utilizes a blend of sophisticated methodologies to tackle the inherent challenges posed by uneven data distributions. By giving dedicated attention to the minority classes, our model demonstrates exceptional proficiency in detecting subtle patterns throughout the different phases of AD, resulting in improved accuracy and a decrease in misclassifications.

By conducting extensive experiments using a variety of datasets gathered from multiple clinical facilities, our innovative architecture consistently demonstrated superior performance compared to established methods in AD classification. Notably, we attained an outstanding accuracy rate of 99.88% on the five-class dataset and 99.58% on the four-class dataset. These findings underscore the effectiveness of our approach in providing precise and dependable predictions across different stages of AD and Dementia.

As we confront the complexities associated with neurodegenerative conditions, the groundbreaking advancements achieved by our framework align with the increasing need to enhance the well-being of individuals impacted by AD and similar cognitive disorders. Through the utilization of Artificial Intelligence and DL, our aim is to inaugurate a fresh era characterized by early disease identification, personalized medical treatments, and enhanced results for patients, all in our determined endeavor to combat AD and Dementia.

Author contributions

Neetha P U: Conceptualization, Software, Field study, Writing-Original draft preparation. **Simran S:** Methodology, Data curation, Writing-Original draft preparation, Software. **Pushpa C N:** Visualization, Validation. **Thriveni J:** Investigation, Writing-Reviewing and Editing. **Venugopal K R:** Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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